autogluon_each_location

October 21, 2023

1 Config

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*5
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

to_drop = []#"snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
 ↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
 ↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
 ↪gm3", "air_density_2m:kgm3"]#, "msl_pressure:hPa", "pressure_50m:hPa", ␣
 ↪"pressure_100m:hPa"]

#to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:
 ↪ms",␣"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:
 ↪cm",␣"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:
 ↪mm",␣"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm",␣
 ↪"absolute_humidity_2m:gm3", "air_density_2m:kgm3"]

use_groups = False
n_groups = 8

auto_stack = False
num_stack_levels = 0
num_bag_folds = 8
num_bag_sets = 20

use_tune_data = True
```

```
use_test_data = True
tune_and_test_length = 0.5 # 3 months from end
holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False#
sample_weight_estimated = 1
sample_weight_may_july = 1

run_analysis = False

shift_predictions_by_average_of_negatives_then_clip = False
clip_predictions = True
shift_predictions = False
```

2 Loading and preprocessing

[2]:
```
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
               'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
               'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    # Filter rows where index.minute == 0
    X_shifted = X[X.index.minute == 0][columns].copy()

    # Create a set for constant-time lookup
    index_set = set(X.index)
```

```
    # Vectorized time shifting
    one_hour = pd.Timedelta('1 hour')
    shifted_indices = X_shifted.index + one_hour
    X_shifted.loc[shifted_indices.isin(index_set)] = X.
↪loc[shifted_indices[shifted_indices.isin(index_set)]][columns]

    # Count
    count1 = len(shifted_indices[shifted_indices.isin(index_set)])
    count2 = len(X_shifted) - count1

    print("COUNT1", count1)
    print("COUNT2", count2)

    # Rename columns
    X_old_unshifted = X_shifted.copy()
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
↪columns]

    date_calc = None
    # If 'date_calc' is present, handle it
    if 'date_calc' in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']




    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
```

```
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
 ↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600
```

```
        X_train_estimated["estimated_diff_hours"] =␣
↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
↪right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
```

```python
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Processing location C…
```

```
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
```

2.1 Feature enginering

2.1.1 Remove anomalies

[3]:
```python
import numpy as np
import pandas as pd


# loop thorugh x train[y], keep track of streaks of same values and replace␣
↪them with nan if they are too long
# also replace nan with 0

import numpy as np

def replace_streaks_with_nan(df, max_streak_length, column="y"):
    for location in df["location"].unique():
        x = df[df["location"] == location][column].copy()

        last_val = None
        streak_length = 1
        streak_indices = []
        allowed = [0]
        found_streaks = {}

        for idx in x.index:
            value = x[idx]
            # if location == "B":
            #     continue

            if value == last_val and value not in allowed:
                streak_length += 1
                streak_indices.append(idx)
            else:
                streak_length = 1
```

```
                last_val = value
                streak_indices.clear()

            if streak_length > max_streak_length:
                found_streaks[value] = streak_length

                for streak_idx in streak_indices:
                    x[idx] = np.nan
                streak_indices.clear()  # clear after setting to NaN to avoid␣
↪setting multiple times
        df.loc[df["location"] == location, column] = x

        print(f"Found streaks for location {location}: {found_streaks}")

    return df


# deep copy of X_train into x_copy
X_train = replace_streaks_with_nan(X_train.copy(), 3, "y")
```

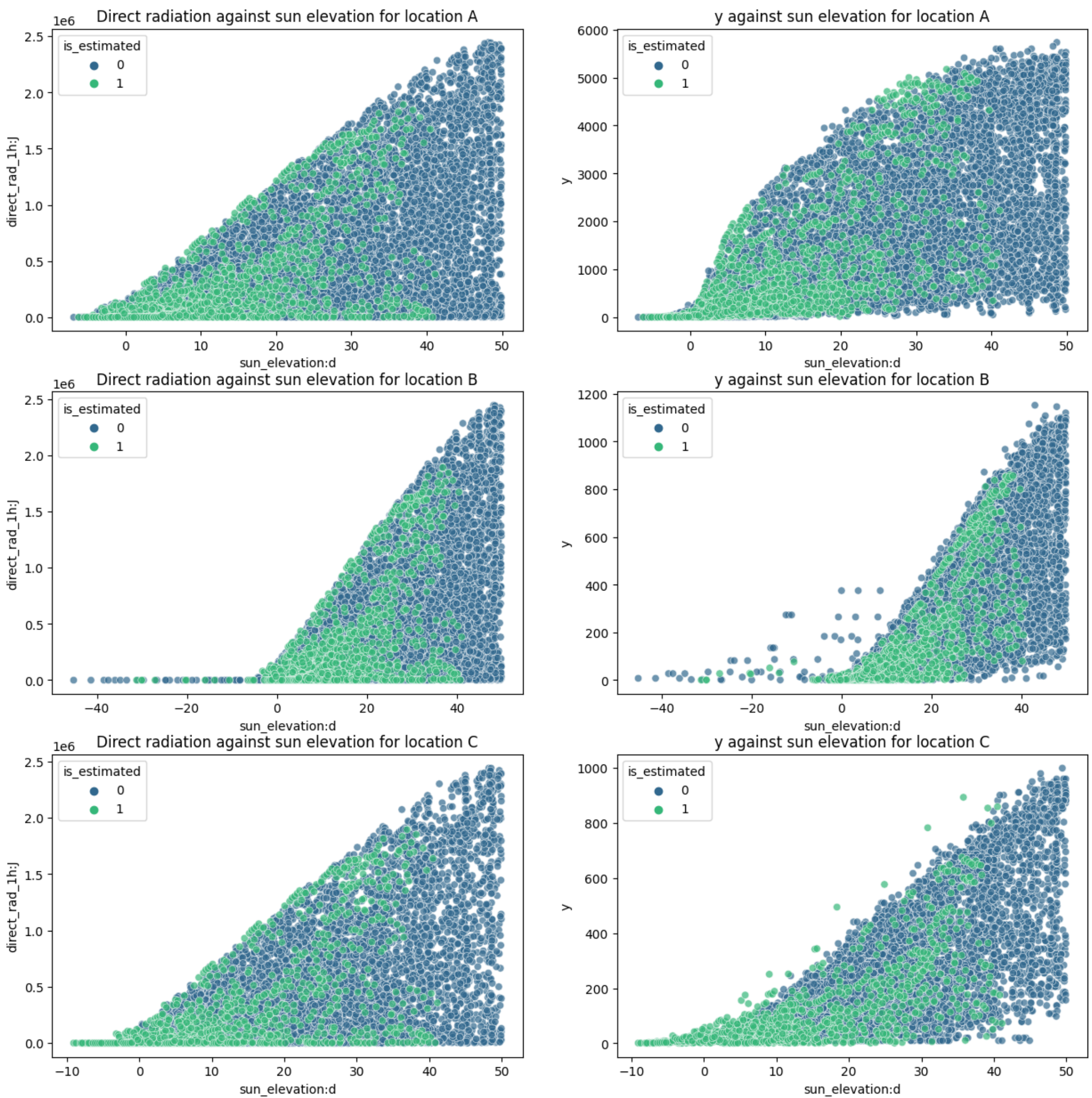
```
Found streaks for location A: {}
Found streaks for location B: {3.45: 28, 6.9: 7, 12.9375: 5, 13.8: 8, 276.0: 78,
18.975: 58, 0.8625: 4, 118.1625: 33, 34.5: 11, 183.7125: 1058, 87.1125: 7,
79.35: 34, 7.7625: 12, 27.6: 448, 273.41249999999997: 72, 264.78749999999997:
55, 169.05: 33, 375.1875: 56, 314.8125: 66, 76.7625: 10, 135.4125: 216, 81.9375:
202, 2.5875: 12, 81.075: 210}
Found streaks for location C: {9.8: 4, 29.400000000000002: 4, 19.6: 4}
```

[4]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  9293
```

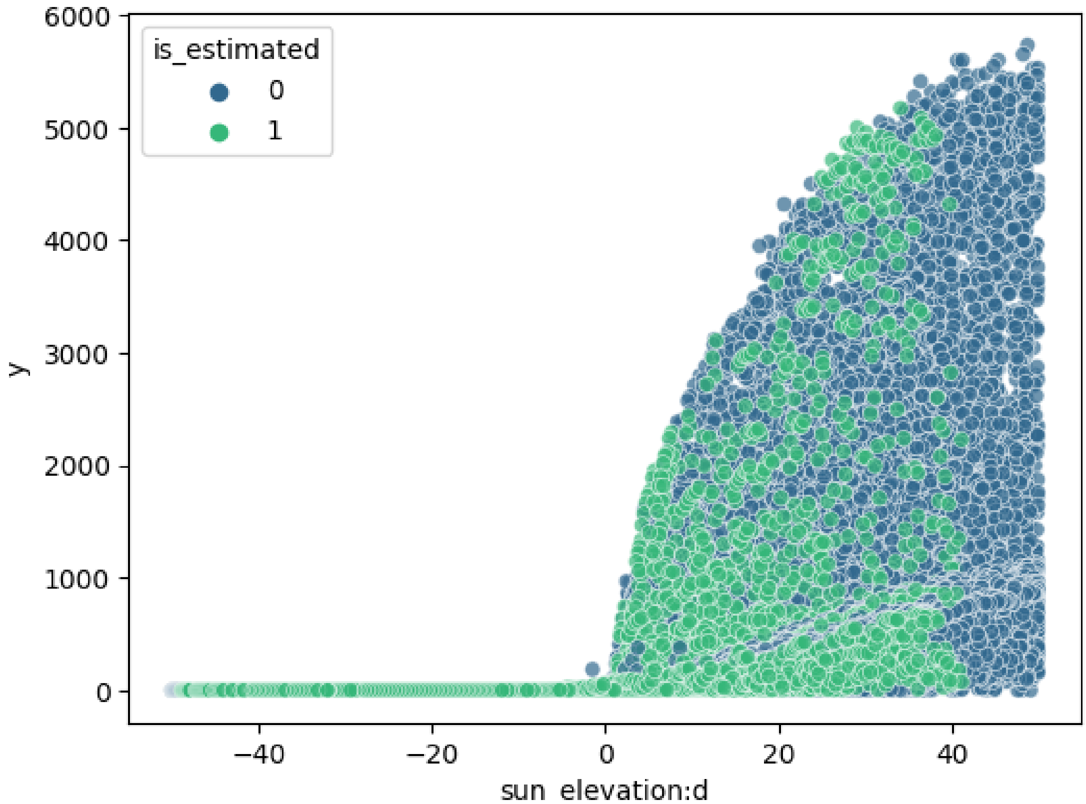
[5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
# Filter out rows where y == 0
temp = X_train[X_train["y"] != 0]

# Plotting
fig, axes = plt.subplots(len(locations), 2, figsize=(15, 5 * len(locations)))

for idx, location in enumerate(locations):
    sns.scatterplot(ax=axes[idx][0], data=temp[temp["location"] == location],␣
↪x="sun_elevation:d", y="direct_rad_1h:J", hue="is_estimated",␣
↪palette="viridis", alpha=0.7)
```

```
    axes[idx][0].set_title(f"Direct radiation against sun elevation for␣
↪location {location}")

    sns.scatterplot(ax=axes[idx][1], data=temp[temp["location"] == location],␣
↪x="sun_elevation:d", y="y", hue="is_estimated", palette="viridis", alpha=0.7)
    axes[idx][1].set_title(f"y against sun elevation for location {location}")

# plt.tight_layout()
# plt.show()
```



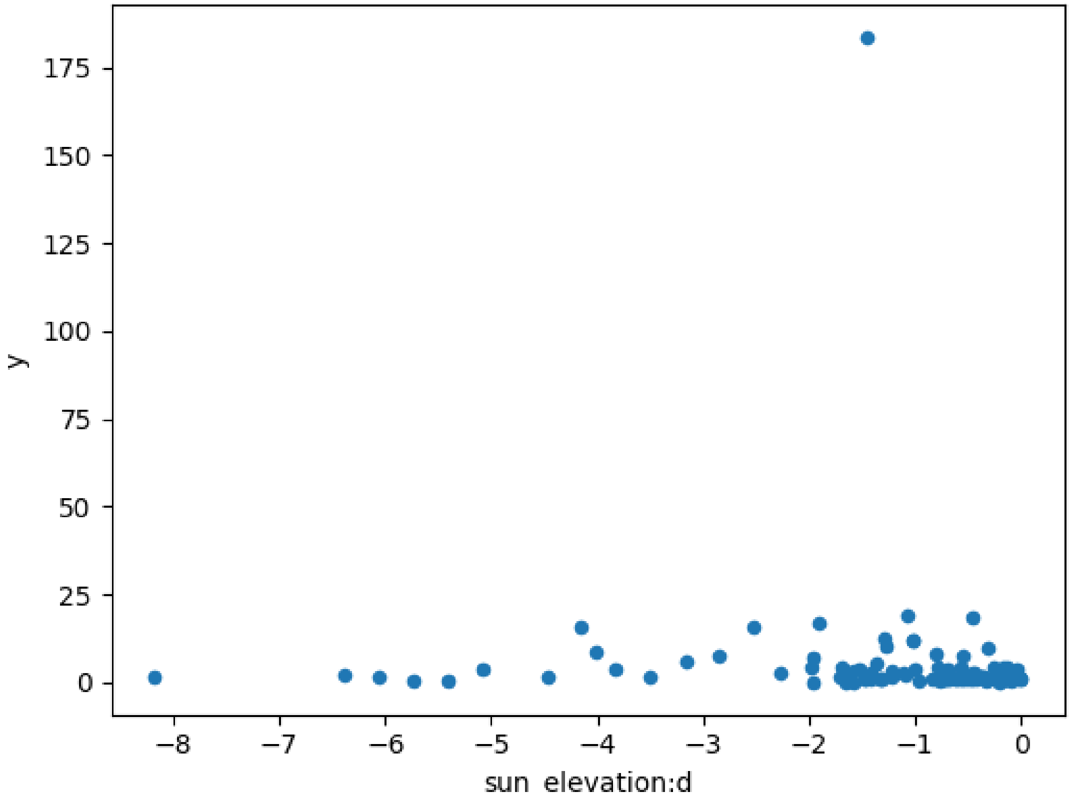

```
[6]: thresh = 0.1
```

```
# Update "y" values to NaN if they don't meet the criteria
mask = (X_train["direct_rad_1h:J"] <= thresh) & (X_train["diffuse_rad_1h:J"] <=␣
 ↪thresh) & (X_train["y"] >= 0.1)
X_train.loc[mask, "y"] = np.nan

# Plot using sns scatterplot
sns.scatterplot(data=X_train, x="sun_elevation:d", y="y", hue="is_estimated",␣
 ↪palette="viridis", alpha=0.7)
plt.show()
```



[7]:
```
# location B count number of rows with y > 0 and sun_elevation:d < 0

condition = (X_train["location"] == "B") & (X_train["y"] > 0) &␣
 ↪(X_train["sun_elevation:d"] < 0)
bad = X_train[condition]

bad.plot.scatter(x="sun_elevation:d", y="y")
```

[7]: <AxesSubplot: xlabel='sun_elevation:d', ylabel='y'>



[8]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  1876
```

2.1.2 Other stuff

[9]:
```
import numpy as np
import pandas as pd

for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

#print(X_train.head())
```

```python
# If the "sample_weight" column is present and weight_evaluation is True, multiply sample_weight with sample_weight_may_july if the ds is between 05-01 00:00:00 and 07-03 23:00:00, else add sample_weight as a column to X_train
if weight_evaluation:
    if "sample_weight" not in X_train.columns:
        X_train["sample_weight"] = 1

    X_train.loc[((X_train.index.month >= 5) & (X_train.index.month <= 6)) | ((X_train.index.month == 7) & (X_train.index.day <= 3)), "sample_weight"] *= sample_weight_may_july


print(X_train.iloc[200])
print(X_train[((X_train.index.month >= 5) & (X_train.index.month <= 6)) | ((X_train.index.month == 7) & (X_train.index.day <= 3))].head(1))



if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups), repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())
```

```python
X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
absolute_humidity_2m:gm3                 7.625
air_density_2m:kgm3                     1.2215
ceiling_height_agl:m               3644.050049
clear_sky_energy_1h:J               2896336.75
clear_sky_rad:W                     753.849976
cloud_base_agl:m                   3644.050049
dew_or_rime:idx                            0.0
dew_point_2m:K                      280.475006
diffuse_rad:W                       127.475006
diffuse_rad_1h:J                    526032.625
direct_rad:W                             488.0
direct_rad_1h:J                    1718048.625
effective_cloud_cover:p              18.200001
elevation:m                                6.0
fresh_snow_12h:cm                          0.0
fresh_snow_1h:cm                           0.0
fresh_snow_24h:cm                          0.0
fresh_snow_3h:cm                           0.0
fresh_snow_6h:cm                           0.0
is_day:idx                                 1.0
is_in_shadow:idx                           0.0
msl_pressure:hPa                   1026.775024
precip_5min:mm                             0.0
precip_type_5min:idx                       0.0
pressure_100m:hPa                  1013.599976
pressure_50m:hPa                   1019.599976
prob_rime:p                                0.0
rain_water:kgm2                            0.0
relative_humidity_1000hPa:p          53.825001
sfc_pressure:hPa                   1025.699951
snow_density:kgm3                          NaN
snow_depth:cm                              0.0
snow_drift:idx                             0.0
snow_melt_10min:mm                         0.0
snow_water:kgm2                            0.0
sun_azimuth:d                       222.089005
sun_elevation:d                      44.503498
```

```
super_cooled_liquid_water:kgm2          0.0
t_1000hPa:K                      286.700012
total_cloud_cover:p               18.200001
visibility:m                       52329.25
wind_speed_10m:ms                       2.6
wind_speed_u_10m:ms                    -1.9
wind_speed_v_10m:ms                   -1.75
wind_speed_w_1000hPa:ms                 0.0
is_estimated                              0
y                                   4367.44
location                                  A
Name: 2019-06-11 13:00:00, dtype: object
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 23:00:00                       7.7               1.2235

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 23:00:00           1689.824951                    0.0

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 23:00:00              0.0       1689.824951              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                     …
2019-06-02 23:00:00      280.299988            0.0               0.0  …

                     t_1000hPa:K  total_cloud_cover:p  visibility:m  \
ds
2019-06-02 23:00:00   286.899994                100.0  33770.648438

                     wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 23:00:00               3.35                -3.35

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 23:00:00                0.275                      0.0

                     is_estimated    y  location
ds
2019-06-02 23:00:00             0  0.0         A

[1 rows x 48 columns]
```

```
[10]: # Create a plot of X_train showing its "y" and color it based on the value of␣
      ↪the sample_weight column.
      if "sample_weight" in X_train.columns:
          import matplotlib.pyplot as plt
          import seaborn as sns
          sns.scatterplot(data=X_train, x=X_train.index, y="y", hue="sample_weight",␣
      ↪palette="deep", size=3)
          plt.show()
```

```
[11]: def normalize_sample_weights_per_location(df):
          for loc in locations:
              loc_df = df[df["location"] == loc]
              loc_df["sample_weight"] = loc_df["sample_weight"] /␣
      ↪loc_df["sample_weight"].sum() * loc_df.shape[0]
              df[df["location"] == loc] = loc_df
          return df

      import pandas as pd

      def split_and_shuffle_data(input_data, num_bins, frac1):
          """
          Splits the input_data into num_bins and shuffles them, then divides the␣
      ↪bins into two datasets based on the given fraction for the first set.

          Args:
              input_data (pd.DataFrame): The data to be split and shuffled.
              num_bins (int): The number of bins to split the data into.
              frac1 (float): The fraction of each bin to go into the first output␣
      ↪dataset.

          Returns:
              pd.DataFrame, pd.DataFrame: The two output datasets.
          """
          # Validate the input fraction
          if frac1 < 0 or frac1 > 1:
              raise ValueError("frac1 must be between 0 and 1.")

          if frac1==1:
              return input_data, pd.DataFrame()

          # Calculate the fraction for the second output set
          frac2 = 1 - frac1

          # Calculate bin size
          bin_size = len(input_data) // num_bins

          # Initialize empty DataFrames for output
```

```
    output_data1 = pd.DataFrame()
    output_data2 = pd.DataFrame()

    for i in range(num_bins):
        # Shuffle the data in the current bin
        np.random.seed(i)
        current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
 ↪sample(frac=1)

        # Calculate the sizes for each output set
        size1 = int(len(current_bin) * frac1)

        # Split and append to output DataFrames
        output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
        output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # Shuffle and split the remaining data
    remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)
    remaining_size1 = int(len(remaining_data) * frac1)

    output_data1 = pd.concat([output_data1, remaining_data.iloc[:
 ↪remaining_size1]])
    output_data2 = pd.concat([output_data2, remaining_data.iloc[remaining_size1:
 ↪]])

    return output_data1, output_data2
```

[12]:

```
from autogluon.tabular import TabularDataset, TabularPredictor
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
 ↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
 ↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
test_set = TabularDataset(data[data["ds"] >= split_time])
```

```
# shuffle test_set and only grab tune_and_test_length percent of it, rest goes␣
 ↪to train_set
test_set, new_train_set = split_and_shuffle_data(test_set, 40,␣
 ↪tune_and_test_length)


print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))
print("Length of test set", len(test_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = None
if use_tune_data:
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            # randomly shuffle the loc_test_set
            loc_tuning_data, loc_test_data =␣
 ↪split_and_shuffle_data(loc_test_set, 40, 0.5)
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
 ↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
 ↪the tuning data.
    if weight_evaluation:
        tuning_data = normalize_sample_weights_per_location(tuning_data)
```

```
else:
    if use_test_data:
        test_data = test_set
        print("Shape of test", test_data.shape[0])


train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
if weight_evaluation:
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
if use_tune_data:
    tuning_data = TabularDataset(tuning_data)
if use_test_data:
    test_data = TabularDataset(test_data)
```

```
Length of train set before adding test set 77247
Length of train set after adding test set 82582
Length of test set 5335
Shapes of tuning and test 2627 2708 5335
```

3 Quick EDA

[13]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
↪label="y", sample=None)
```

[14]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

4 Modeling

[15]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
```

```
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 104
Now creating submission number: 105
New filename: submission_105
```

[16]:
```
predictors = [None, None, None]
```

[17]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
 ↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
 ↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
 ↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
 ↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
 ↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
 ↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
 ↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
 ↪drop(columns=["ds"]),
        time_limit=time_limit,
```

```
        # presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_105_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   90.45 GB / 315.93 GB (28.6%)
Train Data Rows:    30718
Train Data Columns: 47
Tuning Data Rows:    1011
Tuning Data Columns: 47
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 674.18497,
1194.75343)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
```

```
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    128702.77 MB
        Train Data (Original)  Memory Usage: 13.52 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…

Training model for location A…

        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 3): ['elevation:m', 'snow_drift:idx',
'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.2s = Fit runtime
        44 features in original data used to generate 44 features in processed
data.
        Train Data (Processed) Memory Usage: 10.72 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.19s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
```

```
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 299.81s of the
299.81s of remaining time.
        -184.8828        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 299.28s of the
299.28s of remaining time.
        -188.342         = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.43s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 298.74s of the
298.74s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -71.4674         = Validation score   (-mean_absolute_error)
        33.91s   = Training   runtime
        14.62s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 255.49s of the
255.49s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -77.963  = Validation score   (-mean_absolute_error)
        36.98s   = Training   runtime
        14.02s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 213.85s of
the 213.84s of remaining time.
```

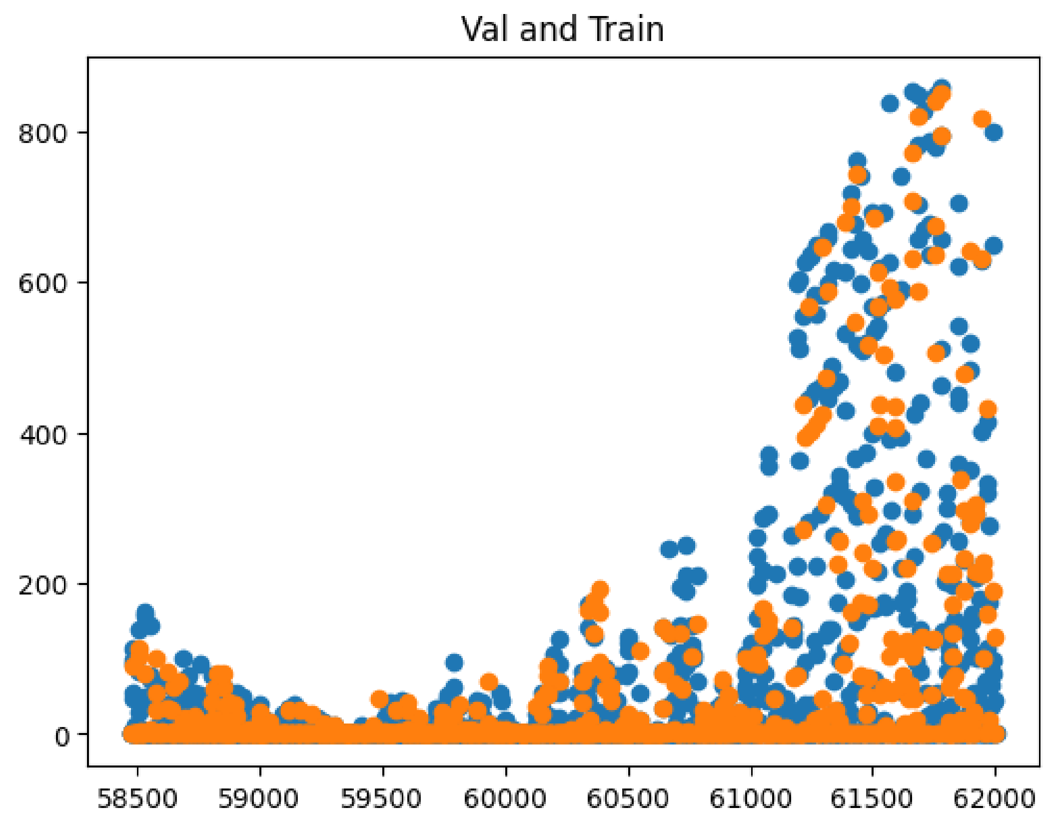
```
        -88.4375         = Validation score   (-mean_absolute_error)
        8.71s    = Training   runtime
        1.13s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 202.85s of the
202.84s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -83.2728         = Validation score   (-mean_absolute_error)
        162.41s  = Training   runtime
        0.18s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 39.23s of the
39.23s of remaining time.
        -92.7594         = Validation score   (-mean_absolute_error)
        1.92s    = Training   runtime
        1.1s     = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 35.05s of the
35.04s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -96.2376         = Validation score   (-mean_absolute_error)
        29.06s   = Training   runtime
        0.49s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 3.49s of the 3.49s of
remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -85.9857         = Validation score   (-mean_absolute_error)
        2.84s    = Training   runtime
        0.21s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 299.81s of the
-1.2s of remaining time.
        -71.01   = Validation score   (-mean_absolute_error)
        0.36s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 301.59s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_105_A/")
Evaluation: mean_absolute_error on test data: -94.48373847625378
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -94.48373847625378,
    "root_mean_squared_error": -261.8831463802315,
    "mean_squared_error": -68582.78235800975,
    "r2": 0.9226288189499688,
```

```
    "pearsonr": 0.9609289284284852,
    "median_absolute_error": -6.1075439453125
}
```

```
Evaluation on test data:
-94.48373847625378
```

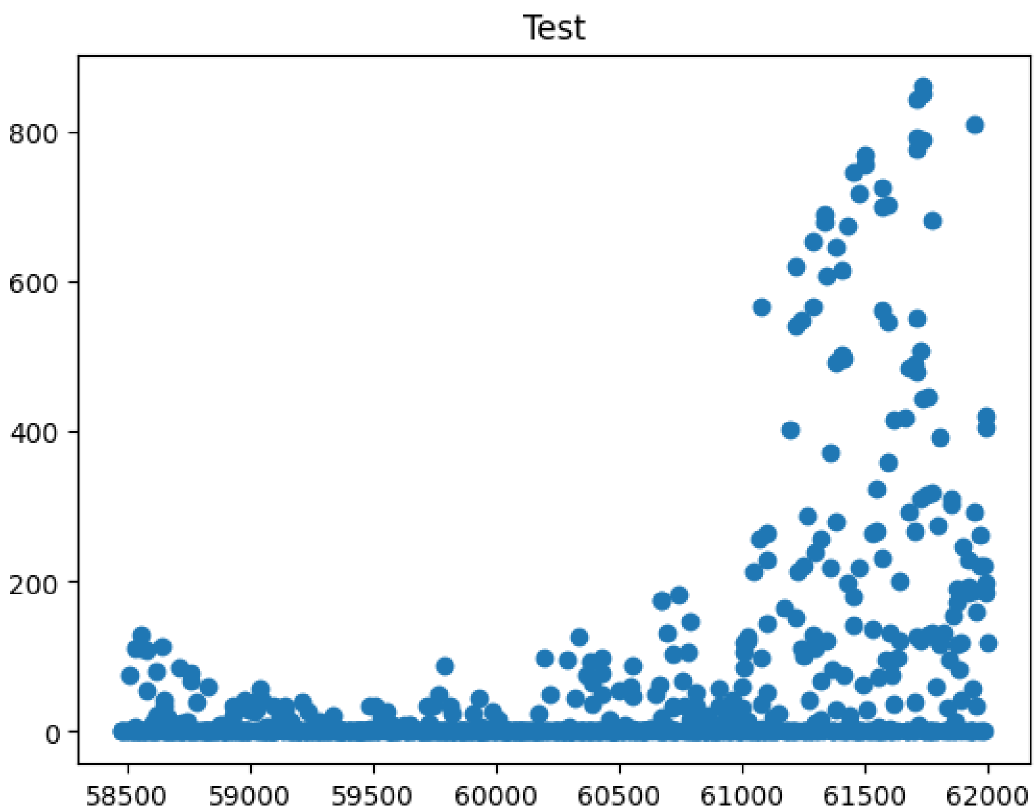
[26]:

```python
import matplotlib.pyplot as plt

leaderboards = [None, None, None]
def leaderboard_for_location(i, loc):
    if use_tune_data:
        plt.scatter(train_data[(train_data["location"] == loc) &␣
 ↪(train_data["is_estimated"]==True)]["y"].index,␣
 ↪train_data[(train_data["location"] == loc) &␣
 ↪(train_data["is_estimated"]==True)]["y"])
        plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,␣
 ↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.title("Val and Train")
        plt.show()

        if use_test_data:
            lb = predictors[i].leaderboard(test_data[test_data["location"] ==␣
 ↪loc])
            lb["location"] = loc
            plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
 ↪test_data[test_data["location"] == loc]["y"])
            plt.title("Test")

            return lb

    return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```




```
                       model  score_test   score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0    KNeighborsUnif_BAG_L1 -368.222750 -184.882756        0.019490       0.402075
0.038327                 0.019490                0.402075           0.038327
1        True          1
1    KNeighborsDist_BAG_L1 -371.848054 -188.342016        0.021856       0.431064
0.037505                 0.021856                0.431064           0.037505
1        True          2
2        LightGBMXT_BAG_L1 -375.079377  -71.467388        1.060233      14.624780
33.906707                1.060233               14.624780          33.906707
1        True          3
3      WeightedEnsemble_L2 -375.479802  -71.010031        2.050362      28.642873
71.243663                0.002636                0.000573           0.359697
2        True         10
4           XGBoost_BAG_L1 -376.391091  -85.985738        0.094854       0.212245
2.844782                 0.094854                0.212245           2.844782
1        True          9
5   RandomForestMSE_BAG_L1 -377.119879  -88.437471        0.555467       1.127844
8.706609                 0.555467                1.127844           8.706609
1        True          5
```

```
6          LightGBM_BAG_L1 -378.678747  -77.962955        0.987493       14.017520
36.977259                 0.987493                14.017520          36.977259
1        True           4
7   NeuralNetFastAI_BAG_L1 -380.855388  -96.237600        0.235412        0.485741
29.058733                 0.235412                 0.485741          29.058733
1        True           8
8     ExtraTreesMSE_BAG_L1 -381.331862  -92.759378        0.559092        1.104659
1.915222                 0.559092                1.104659          1.915222
1        True           7
9          CatBoost_BAG_L1 -382.975098  -83.272843        0.055510        0.177574
162.410531                 0.055510                 0.177574          162.410531
1        True           6
```



[27]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

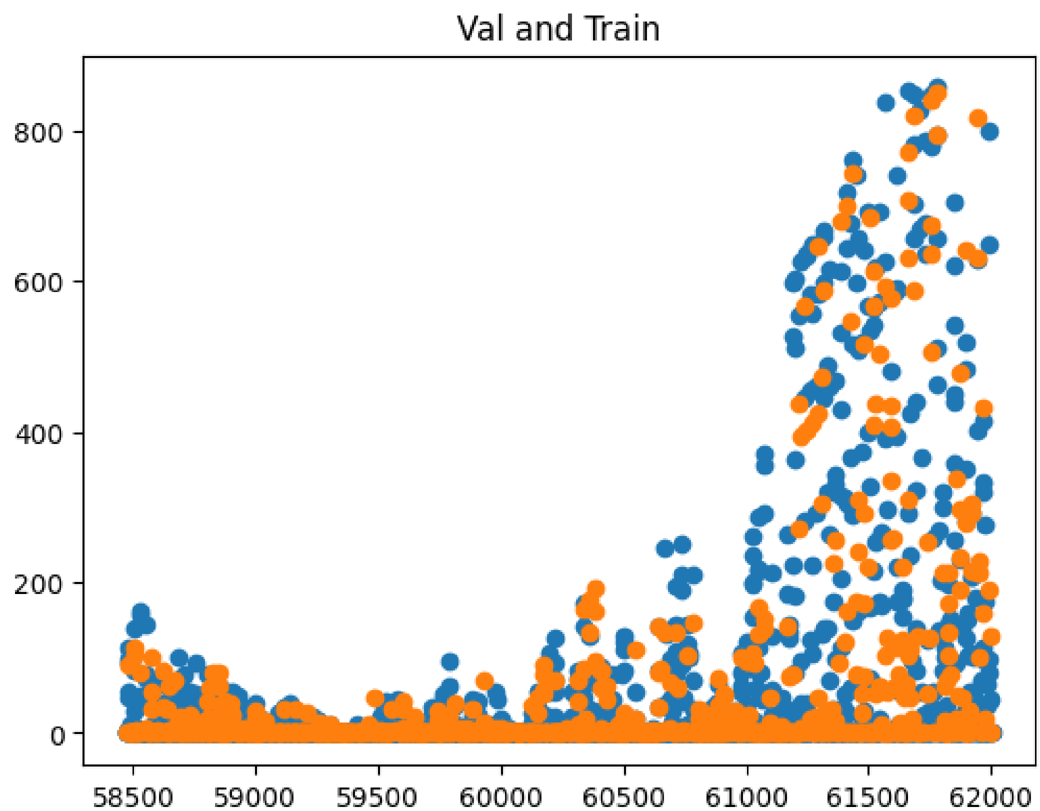
```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_105_B"
Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_105_B/"
AutoGluon Version:  0.8.2
```

```
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   88.32 GB / 315.93 GB (28.0%)
Train Data Rows:    27448
Train Data Columns: 47
Tuning Data Rows:    887
Tuning Data Columns: 47
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 97.84102, 206.22836)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    126567.4 MB
        Train Data (Original)  Memory Usage: 12.07 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…

Training model for location B…

        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
```

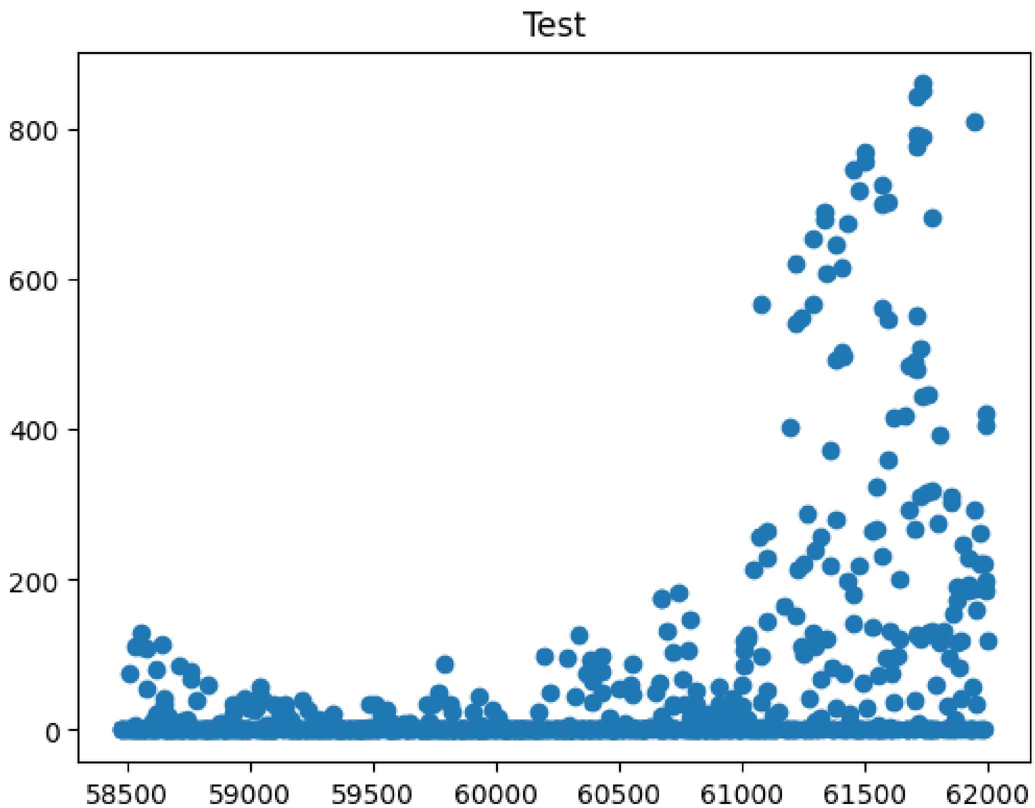
```
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.2s = Fit runtime
        45 features in original data used to generate 45 features in processed
data.
        Train Data (Processed) Memory Usage: 9.8 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.23s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 299.77s of the
299.77s of remaining time.
        -26.647  = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.36s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 299.3s of the
299.3s of remaining time.
        -26.531  = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
```

```
        0.42s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 298.78s of the
298.78s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.5914         = Validation score   (-mean_absolute_error)
        32.3s    = Training   runtime
        13.42s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 261.99s of the
261.99s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.9298         = Validation score   (-mean_absolute_error)
        35.96s   = Training   runtime
        13.31s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 222.03s of
the 222.02s of remaining time.
        -14.1338         = Validation score   (-mean_absolute_error)
        7.08s    = Training   runtime
        0.94s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 212.42s of the
212.42s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3484         = Validation score   (-mean_absolute_error)
        170.65s  = Training   runtime
        0.1s     = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 40.47s of the
40.47s of remaining time.
        -14.1617         = Validation score   (-mean_absolute_error)
        1.61s    = Training   runtime
        0.94s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 36.98s of the
36.98s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.0121         = Validation score   (-mean_absolute_error)
        31.14s   = Training   runtime
        0.46s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 4.4s of the 4.4s of
remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3754         = Validation score   (-mean_absolute_error)
        4.15s    = Training   runtime
        0.26s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 299.77s of the
```

```
-1.09s of remaining time.
        -11.9768         = Validation score   (-mean_absolute_error)
        0.39s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 301.53s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_105_B/")
Evaluation: mean_absolute_error on test data: -13.012663809729608
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -13.012663809729608,
    "root_mean_squared_error": -41.26897798494269,
    "mean_squared_error": -1703.1285439216842,
    "r2": 0.9186700476707049,
    "pearsonr": 0.95860521615639,
    "median_absolute_error": -0.5760937929153442
}

Evaluation on test data:
-13.012663809729608
```



```
                   model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0     WeightedEnsemble_L2  -13.012664 -11.976836        3.424027      29.436049
283.280965                 0.005522                0.000675           0.387428
2       True          10
1       LightGBMXT_BAG_L1  -13.284830 -12.591364        1.088730      13.415638
32.301462                 1.088730               13.415638          32.301462
1       True           3
2  NeuralNetFastAI_BAG_L1  -14.444526 -14.012091        0.232911       0.460278
31.135785                 0.232911                0.460278          31.135785
1       True           8
3         LightGBM_BAG_L1  -14.549384 -12.929780        1.063684      13.311207
35.956331                 1.063684               13.311207          35.956331
1       True           4
4         CatBoost_BAG_L1  -14.786245 -13.348387        0.059539       0.099890
170.654224                 0.059539                0.099890         170.654224
1       True           6
5          XGBoost_BAG_L1  -15.248966 -13.375389        0.095362       0.263699
4.148777                 0.095362                0.263699           4.148777
1       True           9
6    ExtraTreesMSE_BAG_L1  -15.861060 -14.161746        0.447851       0.942284
1.612822                 0.447851                0.942284           1.612822
1       True           7
7  RandomForestMSE_BAG_L1  -16.256785 -14.133810        0.430428       0.942379
7.084136                 0.430428                0.942379           7.084136
1       True           5
8   KNeighborsUnif_BAG_L1  -30.843180 -26.647007        0.021575       0.364292
0.037715                 0.021575                0.364292           0.037715
1       True           1
9   KNeighborsDist_BAG_L1  -31.220652 -26.530970        0.024453       0.421076
0.031165                 0.024453                0.421076           0.031165
1       True           2
```



[ ]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Training model for location C…

Beginning AutoGluon training … Time limit = 300s
AutoGluon will save models to "AutogluonModels/submission_105_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   88.01 GB / 315.93 GB (27.9%)
Train Data Rows:    24416
Train Data Columns: 47
Tuning Data Rows:    729
Tuning Data Columns: 47
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
```

```
        Label info (max, min, mean, stddev): (999.6, 0.0, 80.50393, 169.1834)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    126451.03 MB
        Train Data (Original)  Memory Usage: 10.71 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 3): ['elevation:m', 'snow_drift:idx',
'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.1s = Fit runtime
        44 features in original data used to generate 44 features in processed
data.
        Train Data (Processed) Memory Usage: 8.5 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.17s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
```

```
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 299.83s of the
299.83s of remaining time.
        -21.2159         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.28s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 299.44s of the
299.44s of remaining time.
        -21.2654         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.28s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 299.07s of the
299.07s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.314  = Validation score   (-mean_absolute_error)
        31.24s   = Training   runtime
        11.61s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 263.39s of the
263.39s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.9071         = Validation score   (-mean_absolute_error)
        35.1s    = Training   runtime
```

```
        11.06s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 224.25s of
the 224.25s of remaining time.
        -17.5801         = Validation score   (-mean_absolute_error)
        6.03s    = Training   runtime
        0.82s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 216.67s of the
216.67s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.1475         = Validation score   (-mean_absolute_error)
        173.98s  = Training   runtime
        0.11s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 41.35s of the
41.35s of remaining time.
        -16.3067         = Validation score   (-mean_absolute_error)
        1.36s    = Training   runtime
        0.83s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 38.44s of the
38.44s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")
```

5 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

future_test_data = TabularDataset('X_test_raw.csv')
future_test_data["ds"] = pd.to_datetime(future_test_data["ds"])
#test_data
```

[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
future_test_data_merged = pd.merge(future_test_data, test_ids, how="inner",␣
 ↪right_on=["time", "location"], left_on=["ds", "location"])

#test_data_merged
```

[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
```

```
    "B": 1,
    "C": 2
}
for loc, group in future_test_data.groupby('location'):
    i = location_map[loc]
    subset = future_test_data_merged[future_test_data_merged["location"] ==␣
 ↪loc].reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    #train_data.loc[train_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(train_data[train_data["location"] == loc])
    if use_tune_data:
        tuning_data.loc[tuning_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(tuning_data[tuning_data["location"] == loc])
    if use_test_data:
        test_data.loc[test_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(test_data[test_data["location"] == loc])
```

[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data[train_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="train data")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="tune data")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="test data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    #train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='prediction', ax=ax, label="past predictions")
    #train_data[train_data["location"]==loc].plot(x='ds', y='prediction',␣
 ↪ax=ax, label="past predictions train")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='prediction',␣
 ↪ax=ax, label="past predictions tune")
```

```
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions test")



    # title
    ax.set_title(f"Predictions for location {loc}")
```

[ ]:
```
temp_predictions = [prediction.copy() for prediction in predictions]
if clip_predictions:
    # clip predictions smaller than 0 to 0
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())

# Instead of clipping, shift all prediction values up by the largest negative␣
↪number.
# This way, the smallest prediction will be 0.
elif shift_predictions:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred["prediction"] = pred["prediction"] - pred["prediction"].min()
        print("Smallest prediction after clipping:", pred["prediction"].min())

elif shift_predictions_by_average_of_negatives_then_clip:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        mean_negative = pred[pred["prediction"] < 0]["prediction"].mean()
        # if not nan
        if mean_negative == mean_negative:
            pred["prediction"] = pred["prediction"] - mean_negative

        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())



# concatenate predictions
submissions_df = pd.concat(temp_predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on␣
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
↪index=False)
print("jall1a")
```

[ ]:
```
# feature importance
# print starting calculating feature importance for location A with big text␣
↪font
print("\033[1m" + "Calculating feature importance for location A..." +␣
↪"\033[0m")
predictors[0].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "A"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location B..." +␣
↪"\033[0m")
predictors[1].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "B"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location C..." +␣
↪"\033[0m")
predictors[2].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "C"], time_limit=60*10)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
#subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_automatic_save.pdf"),␣
↪"autogluon_each_location.ipynb"])
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
```

```
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email', 'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push', 'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream', 'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```